# Optimal Cost Reduction in Electric Vehicle's Charge-Discharge Scheduling while Maximizing User Satisfaction

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***Abstract*—**

***Index Terms*—Electric vehicle,**

## I. INTRODUCTION

THe rapid escalation of greenhouse gas (GHG) emissions in the twenty-first century has become a global concern, as it continues to drive the rise in average global temperatures

## II. RELATED WORK

Electric Vehicle (EV) charging scheduling

## III. SYSTEM MODEL AND PROBLEM FORMULATION

### *A. System Overview and terminologies*

We consider a workplace parking lot equipped with $M$ charging points and accommodating $N\ EVs$, where generally $N > M$. Each EV $i \in \mathbb{N} = \{1, 2, \ldots, N\}$ arrives at the parking facility at time $T_i^{\text{arr}}$ and departs at $T_i^{\text{dep}}$, with a maximum battery capacity $E_i^{\text{cap}}$, initial SoC $SoC_i^{init}$ at the time of arrival, expected SoC range $[SoC_i^{min}, SoC_i^{max}]$ where $SoC_i^{max}$ is the prefered energy level with maximum user satisfaction at departure. The system operates over a 12-hour working time from 8 AM to 8 PM, discretized into $T = 48$ equal intervals of 15 min each, indexed by $t \in \mathbb{T} = \{1, 2, \ldots, T\}$.

Let $\mathbb{M} = \{1, 2, \ldots, M\}$ denote the set of available charging points (CP). Each CP supports both charging and discharging (bidirectional operation). The Power limits for each EV are supposed to be in the range between $P_i^{\text{dis,min}}$ and $P_i^{\text{ch,max}}$, with $P_i^{\text{dis,min}} \leq p_{i,t} \leq P_i^{\text{ch,max}}, \quad \forall i \in \mathbb{N}, \forall t \in \mathbb{T}$ where $p_{i,t}$ is the power (positive for charging, negative for discharging) assigned to EV $i$ at time $t$.

The objective is to determine a feasible charging/discharging schedule and CP assignment such that the energy demands of all EVs are met within their stay period. The Overall objective is to minimize a multi-objective cost function comprising system-level cost, battery degradation cost, and grid load variance, while maximizing user satisfaction, ensuring feasibility constraints, and limited charger availability.

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### *B. Net Charging/Discharging Cost Model*

Each EV $i$ pays for the energy it consumes (charging) and generate revenue for the energy it gives back to the grid (discharging), based on the time of use electricity price $\pi_t$ (in \$/kWh) and discharging revenue rate $\pi_t^{\text{rev}}$ (in \$/kWh) at each time slot $t$. We aim to minimize the total energy cost incurred due to EV charging and discharging during its stay, while dynamically assigning chargers and ensuring that charging and discharging do not occur simultaneously. To ensure only actively connected EVs are considered, we define the charger assignment indicator $z_{m,i,t} \in \{0, 1\}$, which equals 1 if EV $i$ is assigned to charger $m$ at time $t$. The net cost function is defined as:

$$F_1(p_{i,t}, z_{m,i,t}) = \sum_{i=1}^{N} \sum_{t=1}^{T} \Big( \pi_t^{buy} \cdot \max(p_{i,t}, 0) + \pi_t^{\text{rev}} \cdot \min(p_{i,t}, 0) \Big) \cdot \Delta t \cdot \Big( \sum_{m=1}^{M} z_{m,i,t} \Big) \quad (1)$$

where: $p_{i,t}$ is the power (positive for charging, negative for discharging) assigned to EV $i$ at time $t$, $\Delta t$ is the duration of each time slot (in hours), and this value $\sum_{m=1}^{M} z_{m,i,t} = 1$ ensures whether $EV_i$ is connected to any charger at time $t$.

*1) Battery Degradation Cost Model:* Battery degradation is a critical factor in long-term EV operation and V2G economics. Frequent charging and discharging cycles accelerate battery wear, reducing the usable capacity and shortening the overall battery lifespan. To calculate this, we model the degradation cost as a function of the total absolute energy exchanged by the EV during charging/discharging.

The total degradation cost for all EVs over the scheduling horizon is defined as:

$$F_2(p_{i,t}, z_{m,i,t}) = \sum_{i=1}^{N} \sum_{t=1}^{T} c_i^{\text{deg}} \cdot |p_{i,t}| \cdot \Delta t \cdot \left( \sum_{m=1}^{M} z_{m,i,t} \right) \quad (2)$$

where $|p_{i,t}|$ captures both charging and discharging energy, which ensures that both charging and discharging are penalized equally, as both contribute to battery aging regardless of direction. Here, $c_i^{\text{deg}}$ is a degradation cost coefficient (in \$/kWh) that quantifies the estimated long-term cost of battery wear per unit of energy transferred, defined as:

$$c_i^{\text{deg}} = \frac{C_i^{\text{battery}}}{L_i^{\text{cycle}} \times E_i^{\text{cap}}} \quad (3)$$

where $C_i^{\text{battery}}$ represents the battery replacement cost of EV $i$ (in \$), $L_i^{\text{cycle}}$ denotes the battery cycle life of EV $i$ measured in full cycles, and $E_i^{\text{cap}}$ is the battery capacity of EV $i$ in kWh. The coefficient $c_i^{\text{deg}}$ gives the battery degradation cost per kWh for EV $i$ (in \$/kWh). For example, if $C_i^{\text{battery}} = 3,00,000$ \$, $L_i^{\text{cycle}} = 10000$ cycles, and $E_i^{\text{cap}} = 60$ kWh, then $c_i^{\text{deg}} = \frac{3,00,000}{10000\times 60} = 0.5$ \$/kWh. This value gives the effective degradation cost of the battery for every kWh of energy charged or discharged.

### C. Grid Load Variance Model

The grid load variance computes fluctuations in the aggregated EV load over the scheduling horizon defined as:

$$F_3(p_{i,t}) \;=\; \sum_{t=1}^{T}\big(L_t - \bar{L}\big)^2 \;=\; \sum_{t=1}^{T}\left(\sum_{i=1}^{N} p_{i,t} - \frac{1}{T}\sum_{t'=1}^{T}\sum_{i=1}^{N} p_{i,t'}\right)^2 . \tag{4}$$

where, $p_{i,t}$ denotes the net power of EV $i$ at time slot $t$, the total EV load $L_t$ at time $t$ and the average load $\bar{L}$ across $T$ slots are given as follows:

$$L_t \;=\; \sum_{i=1}^{N} p_{i,t}, \tag{5}$$

$$\bar{L} \;=\; \frac{1}{T}\sum_{t'=1}^{T}\sum_{i=1}^{N} p_{i,t'}. \tag{6}$$

The equation 4 measures how much the total demand from EV charging and discharging changes over time. A high variance means there are sharp peaks and dips in the load curve, while a low variance indicates a smoother and more stable demand. For system operators, keeping this variance low is important for reliable and efficient grid operation. In EV scheduling, this term links all EVs by encouraging them to avoid charging at the same time. By penalizing large demand fluctuations, it promotes off-peak and staggered charging, helping to balance the overall load.

### D. User Sensitivity and Satisfaction Model

In the context of coordinated EV charging, user satisfaction refers to how closely the achieved SoC at the end of the charging schedule. The idea is that the closer an EV reaches its maximum SoC, the more satisfied the user will be. On arrival, we quantify each user's sensitivity (urgency) by SoC required to reach the vehicle's maximum acceptable SoC within the parked duration. Below are the steps to calculate satisfaction score $S_i \in [0,1]$ for each EV $i$ based on the urgency of its charging requirement.

*Step 1: Energy required to meet target SoC:* Let $\text{SoC}_i^{\text{init}}$, $\text{SoC}_i^{\max}$, and $\text{SoC}_{i,T}$ denote the arrival, target, and final SoC, respectively. Also, we have $E_i^{\text{cap}}$ (kWh) be the battery capacity, then required energy to reach the target $\text{SoC}_i^{\max}$ will be:

$$E_i^{\text{req}} = \max\big(0,\ \text{SoC}_i^{\max} - \text{SoC}_i^{\text{init}}\big) \times E_i^{\text{cap}} \tag{7}$$

*Step 2: Average power requirement:* Let $T_i^{\text{arr}}$ and $T_i^{\text{dep}}$ denote the arrival and departure times (in hours), and:

$$T_i^{\text{stay}} = T_i^{\text{dep}} - T_i^{\text{arr}} \tag{8}$$

The average charging power needed to meet the target within the stay duration is:

$$P_i^{\text{req}}(t) = \begin{cases} \frac{E_i^{\text{req}}}{T_i^{\text{stay}}}, & T_i^{\text{stay}} > 0, \\ \infty, & \text{if } T_i^{\text{stay}} = 0 \text{ and } E_i^{\text{req}} > 0 \end{cases} \tag{9}$$

*Step 3: sensitivity calculation:* Let $P_{\text{ref}} > 0$ be a reference charging power (e.g., typical charger rating). The normlized sensitivity is then defined as:

$$\phi_i = \min\left(1,\ \frac{P_i^{\text{req}}(t)}{P_{\text{ref}}}\right), \quad \phi_i \in [0,1] \tag{10}$$

*Step 4: Normalized SoC deviation on departure:* If the target SoC does not met, the normalized SoC deviation is:

$$\delta_i = \begin{cases} 0, & \text{SoC}_{i,T} \ge \text{SoC}_i^{\max}, \\ \frac{\text{SoC}_i^{\max} - \text{SoC}_{i,T}}{\text{SoC}_i^{\max} - \text{SoC}_i^{\text{init}}}, & \text{SoC}_{i,T} < \text{SoC}_i^{\max} \end{cases} \tag{11}$$

where the denominator is assumed $> 0$ for simplicity; it means Evs will always arrives with lesser SoC than target SoC.

*Step 5: Satisfaction score:* Finally, the satisfaction score is computed as:

$$S_i = \max\left(0,\ 1 - \phi_i\,\delta_i\right) \tag{12}$$

*Example:* For $E_i^{\text{cap}} = 60\,\text{kWh}$, $\text{SoC}_i^{\text{init}} = 0.20$, $\text{SoC}_i^{\max} = 0.90$, $T_i^{\text{stay}} = 5\,\text{h}$, and $P_{\text{ref}} = 7\,\text{kW}$:

$$\begin{aligned} E_i^{\text{req}} &= 0.70 \times 60 = 42 \text{ kWh}, \\ P_i^{\text{req}}(t) &= 42/5 = 8.4 \text{ kW}, \\ \phi_i &= \min(1, 8.4/7) = 1, \\ \delta_i &= (0.90 - 0.50)/(0.90 - 0.20) \approx 0.5714, \\ S_i &\approx 1 - (1)(0.5714) \approx 0.429. \end{aligned}$$

This $S_i \approx 0.429$. shows that, user is 42% satisfied, as it needs more power (i.e 8.4KW) to reach the target, but it is not possible because it is greater than rated power rating. hence it get overall 40% reduced SoC on departure. since, our objective is to maximize the total satisfaction of all EVs after the charging/discharging scheduling is done, it can be formally defined as:

$$F_4(\text{SoC}_{i,T}) \;=\; \sum_{i=1}^{N} S_i \tag{13}$$

## IV. MultiObjective problem Formulation for EV charging/discharging

### A. Decision variables and notation

**Definition 1** (Charger-assignment variable)**.** *It is a binary variable that indicates whether EV $i$ is assigned to charger $m$ at time $t$:*

$$z_{m,i,t} = \begin{cases} 1: & \textit{if } EV_i \textit{ is assigned to charger } m \textit{ at slot } t, \\ 0: & \textit{otherwise.} \end{cases} \tag{14}$$

**Definition 2** (Power variable)**.** *It is the net power (kW) assigned to EV $i$ at time slot $t$:*

$$p_{i,t} \in \mathbb{R}, \qquad \begin{cases} p_{i,t} > 0: & \textit{charging}, \\ p_{i,t} < 0: & \textit{discharging}. \end{cases} \tag{15}$$

**Definition 3** (State-of-charge (SoC))**.** *It is the state-of-charge of EV $i$ at the end of slot $t$:*

$$\mathrm{SoC}_{i,t} \in [0,1], \tag{16}$$

### B. Objective functions

Using the above decision variables, we define four objectives which are simultaneously minimized

1) *minimization of Net charging/discharging cost :*

$$F_1(p_{i,t}, z_{m,i,t}) = \min \sum_{i=1}^{N}\sum_{t=1}^{T} \Big(\pi_t \cdot \max(p_{i,t},0) + \pi_t^{\text{rev}} \cdot \min(p_{i,t},0)\Big) \cdot \Delta t \cdot \Big(\sum_{m=1}^{M} z_{m,i,t}\Big) \tag{17}$$

2) *minimization of battery degradation cost :*

$$F_2(p_{i,t}, z_{m,i,t}) = \min \sum_{i=1}^{N}\sum_{t=1}^{T} c_i^{\text{deg}}\, |p_{i,t}|\, \Delta t \times \Big(\sum_{m=1}^{M} z_{m,i,t}\Big). \tag{18}$$

3) *Minimization of Grid load variance:*

$$F_3(p_{i,t}) = \min \sum_{t=1}^{T} \Big(L_t - \bar{L}\Big)^2, \qquad L_t = \sum_{i=1}^{N} p_{i,t}, \qquad \bar{L} = \frac{1}{T}\sum_{t'=1}^{T}\sum_{i=1}^{N} p_{i,t'}. \tag{19}$$

4) *Maximization of total user satisfaction :* when $S_i \in [0,1]$ be the satisfaction of EV $i$ (higher is better). We minimize negative satisfaction.

$$F_4(\mathrm{SoC_{i,T}}) = -\min \sum_{i=1}^{N} S_i(\mathrm{SoC}_{i,T}). \tag{20}$$

- **Constraints:** To ensure feasible and reliable EV charging and discharging schedules, we define the following set of constraints that support the previously described multi-objective cost function.

  **C1** : $P_i^{\text{dis,min}} \le p_{i,t} \le P_i^{\text{ch,max}}, \quad \forall i,t$
  **C2** : $\sum_{m=1}^{M} z_{m,i,t} \le 1 \quad \forall i,t$
  **C3** : $\sum_{i=1}^{N} z_{m,i,t} \le 1 \quad \forall m,t$
  **C4** : $p_{i,t} = 0, \quad \text{if } \sum_{m=1}^{M} z_{m,i,t} = 0$
  **C5** : $\mathrm{SoC}_i^{\min} \le \mathrm{SoC}_{i,t} \le \mathrm{SoC}_i^{\max}$
  **C6** : $\sum_{j\in\mathcal{C}} p_j^{req}(t) \le P_{max}$

The interpretation of the above constraints is in order. Constraint **C1** restricts the charging and discharging power of each EV within its allowable physical limits. This ensures that no EV exceeds its maximum charging capability or discharging rate. **C2** enforces that an EV can occupy at most one charger in a given time slot. **C3** guarantees that each charger can serve only one EV at a time. **C4** links the power decision with charger allocation. If an EV is not assigned to any charger, its charging or discharging power must be zero. **C5** maintains the SoC of each EV within safe operational limits throughout the scheduling horizon, thereby preventing both overcharging and excessive battery depletion. **C6** ensures that the aggregate charging demand of all connected EVs at any slot does not exceed the grid's maximum capacity.

### C. Weighted sum multiobjective problem formulation problem

To combine the four objectives into a single problem, each objective value $F_k$ is first normalized and set of non-negative weights $w_k$ is assigned to each objective, such that $\sum_{k=1}^{4} w_k = 1$, where the weights represent the relative importance of each objective according to the preferences. The weighted-sum optimization problem can then be expressed as:

$$\begin{aligned} \min \quad & J(p_{i,t}, z_{m,i,t}, \mathrm{SoC_{i,T}}) = \sum_{k=1}^{4} w_k\, F_k \\ \text{subject to} \quad & \text{constraints C1–C5,} \end{aligned} \tag{21}$$

### D. Problem statement

Given $\{N, M, T\}$, EV parameters $E_i^{\text{cap}}, \mathrm{SoC}_i^{\text{init}}, \mathrm{SoC}_i^{\max}, P_i^{\text{ch,max}}, P_i^{\text{dis,min}}\}$, energy prices $\{\pi_t, \pi_t^{\text{rev}}\}$ and user requirements, find $\{p_{i,t}, z_{m,i,t}, \mathrm{SoC}_{i,t}\}$ that minimize $J$ in (21) subject to C1–C5.

## V. Propsed Two Stage Scheduling Framework

In order to solve the formulated EV charging/discharging scheduling problem in workplace parking, a two-stage scheduling framework is proposed. The first stage applies a priority-based scheduling algorithm to ensure fairness and urgency-aware charger assignment. The second stage refines the power allocation through a Genetic Algorithm (GA), minimizing costs and grid variance while maximizing user satisfaction. In order to set the foundation for comprehending the proposed framework, this section first discusses the background of priority scheduling and GA signifying the selection of these particular state of the art methods in this context.

### A. Stage-I: Priority Scheduling

Priority scheduling is a classical real-time decision-making approach that ranks competing tasks according to defined priority criteria. It is lightweight, interpretable scheduling algorithm that can be used to decide which vehicles should access limited charging points at any given time, especially when the number of EVs exceeds available chargers. In the considered workplace parking scenario, EV users typically have common arrival and departure times, limited plug-in duration, and heterogeneous

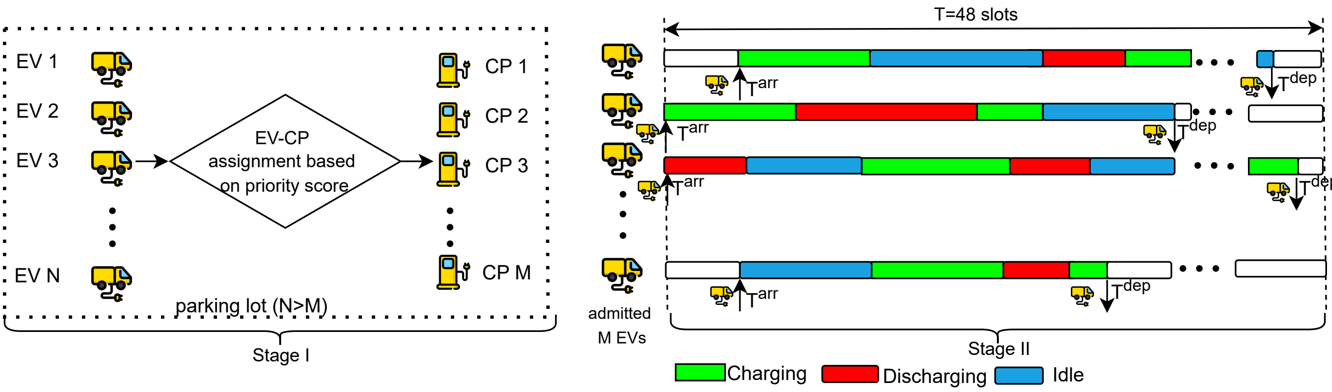


Fig. 1: Two stage scheduling of EV in Parking lot

energy requirements. A priority scheduling mechanism is therefore well suited for resolving charger assignment, ensuring urgent EVs are not left unserved. At the beginning of each slot $t$, a *priority score* $\lambda_i(t)$ is assigned to each EV $i$. The score reflects urgency, expected degradation, grid load conditions,and normalized price factor and is expressed as

$$\lambda_i(t) = w_s\phi_i(t) - w_d D_i^{\text{factor}}(t) - w_g G_t^{\text{factor}}(t) - w_p\, P_t^{\text{factor}} \tag{22}$$

where $w_s, w_d, w_g, w_p$ are non-negative weight coefficients with $w_s + w_d + w_g + w_p = 1$. Urgency factor $\phi_i(t)$ represents the urgency of EV $i$ in achieving its target SoC before departure. It is derived from the satisfaction model defined above as $\phi_i(t) = \frac{p_i^{req}(t)}{p^{ref}}$, where $p^{ref}$ is the charger rating, and $p_i^{req}(t)$ is the required average charging power for $EV_i$ to reach its target SoC before departure. Degradation factor $D_i^{\text{factor}}(t)$ quantifies the expected contribution of $EV_i$ to battery wear during charging/discharging. It is expressed as a normalized indicator calculated as

$$D_i^{\text{factor}}(t) = \frac{c_{\text{deg}} \cdot \Delta E_i - \min_j\left(c_{\text{deg}} \cdot \Delta E_j\right)}{\max_j\left(c_{\text{deg}} \cdot \Delta E_j\right) - \min_j\left(c_{\text{deg}} \cdot \Delta E_j\right)} \tag{23}$$

where $c_{\text{deg}}$ is the degradation cost coefficient defined above, $\Delta E_i$ represents the maximum energy requirement, while *index j* explicitly states that $j$ iterates over all EVs in slot $t$. Grid stress factor $G_t^{\text{factor}}(t)$ is a system-level measure of aggregate charging demand relative to grid power limits, defined as

$$G_t^{\text{factor}}(t) = \max\left(0,\ \frac{\widehat{P}_{agg}(t) - \overline{P}(t)}{P_{max} - \overline{P}(t)}\right) \tag{24}$$

where $\widehat{P}_{agg}(t) = \sum_{j \in \mathcal{C}} p_j^{req}(t)$ is the estimated aggregate demand of all connected EVs $\mathcal{C}$, and $\overline{P}(t)$ is the average load profile, while $P_{max}$ is the grid maximum operational power capacity. The value of $G_t^{\text{factor}}$ will remain same for all EV in first slot. The price factor $P_t^{\text{factor}}$ is obtained by normalizing the current price (including charging price $\pi_t^{buy}$ and discharging price $\pi_t^{\text{rev}}$) using their respective tariff ranges:

$$P_t^{\text{buy}} = \frac{\pi_t^{buy} - \pi_{\text{min}}^{\text{buy}}}{\pi_{\text{max}}^{\text{buy}} - \pi_{\text{min}}^{\text{buy}}}, \qquad P_t^{\text{rev}} = \frac{\pi_t^{\text{rev}} - \pi_{\text{min}}^{\text{rev}}}{\pi_{\text{max}}^{\text{rev}} - \pi_{\text{min}}^{\text{rev}}}. \tag{25}$$

These two normalized price terms are then combined into a single price factor

$$P_t^{\text{factor}} = P_t^{\text{buy}} - P_t^{\text{rev}}, \quad P_t^{\text{factor}} \in [-1, 1] \tag{26}$$

which is positive when charging is relatively expensive (discouraging further charging) and negative when discharging is attractive (encouraging V2G participation). The price tfactor is system-level and identical for all EVs in slot $t$.

*Assignment rule:* EVs are ranked in descending order of $\lambda_i(t)$, and the top $M$ EVs are granted charger access. The connected EV will remain plugged unless release conditions are satisfied (i.e., target SoC is achieved, departure time arrives). Waiting EVs are admitted only when chargers are released.

*1) Numerical example (Stage-I):* No. of EVs = 3 and chargers = 2 with given system parameters and EV states shown in table I as follows:

- Slot duration: $\Delta t = 0.25$ h;
- Grid: $P_{\max} = 25$ kW, average load $\overline{P}(t) = 12$ kW.
- Degradation coefficient: $c_{\text{deg}} = 0.02$ \$/kWh.
- Tariffs: $\pi_t^{buy} = 0.25$ \$/kWh, $\pi_t^{\text{rev}} = 0.18$ \$/kWh.
- Price ranges: $[\pi_{\text{min}}^{\text{buy}}, \pi_{\text{max}}^{\text{buy}}] = [0.10, 0.50]$, $[\pi_{\text{min}}^{\text{rev}}, \pi_{\text{max}}^{\text{rev}}] = [0.05, 0.30]$.
- $w_s = w_d = w_g = w_p = 0.25$(choosen equal for showing calculations)

TABLE I: EV states for the example

| EV | $E_i^{\text{cap}}$ (kWh) | $SoC_{init}$ | $SoC_i^{\max}$ | $P_{ref}$ (kW) | $T_i^{\text{stay}}$ (h) |
|---|---|---|---|---|---|
| EV1 | 60 | 0.30 | 0.80 | 7 | 4.0 |
| EV2 | 40 | 0.60 | 0.90 | 11 | 1.0 |
| EV3 | 50 | 0.20 | 0.60 | 7 | 6.0 |

*a) Step 1 — Urgency factor:* Remaining energy required using equation 7

$$\Delta E_1 = 30 \text{ kWh}, \quad \Delta E_2 = 12 \text{ kWh}, \quad \Delta E_3 = 20 \text{ kWh}.$$

Required average power using equation 9 :

$$p_1^{\text{req}} = 7.00 \text{ kW}, \quad p_2^{\text{req}} = 11.00 \text{ kW}, \quad p_3^{\text{req}} = 3.33 \text{ kW}.$$

Urgency factor using equation 10:

$$\phi_1 = 1.0, \ \phi_2 = 1.0, \ \phi_3 = 0.476.$$

*b) Step 2 — Degradation factor for $EV_i = c_{deg}\Delta E_i$:*

$$c_{\text{deg}}\Delta E_1 = 0.600, \ c_{\text{deg}}\Delta E_2 = 0.240, \ c_{\text{deg}}\Delta E_3 = 0.400.$$

Normalize $D_i^{\text{factor}}$ for each EV using equation 23 :

$$D_1 = 1.000, \ D_2 = 0.000, \ D_3 = 0.444.$$

*c) Step 3 — Grid stress factor:* Aggregate demand:

$$\widehat{P}_{agg} = \sum_j p_j^{\text{req}} = 21.3333 \text{ kW}.$$

$$G_t^{\text{factor}} = \frac{\widehat{P}_{agg} - \overline{P}}{P_{\max} - \overline{P}} = \frac{21.3333 - 12}{25 - 12} = 0.7179.$$

*d) Step 4 — Price factor:* Normalize charge and discharge prices:

$$P_t^{\text{buy}} = \frac{0.25 - 0.10}{0.40} = 0.375, P_t^{\text{rev}} = \frac{0.18 - 0.05}{0.25} = 0.520.$$

Single price factor:

$$P_t^{\text{factor}} = P_t^{\text{buy}} - P_t^{\text{rev}} = 0.375 - 0.520 = -0.145.$$

*e) Step 5 — Priority score for each EV:*

$$\lambda_i(t) = 0.25\phi_i - 0.25D_i - 0.25G_t^{\text{factor}} - 0.25P_t^{\text{factor}}.$$

**For EV1:**

$$\lambda_1 = 0.2500 - 0.2500 - 0.17949 + 0.03625 = -0.14324.$$

**For EV2:**

$$\lambda_2 = 0.2500 + 0.0000 - 0.17949 + 0.03625 = 0.10676.$$

**For EV3:**

$$\lambda_3 = 0.11905 - 0.11111 - 0.17949 + 0.03625 = -0.13530.$$

*f) Step 6 — Sorting of EVs and admission:* The priority scores are:

$$\lambda_2 = 0.10676 > \lambda_3 = -0.13530 > \lambda_1 = -0.14324.$$

After sorting in descending order with $M = 2$ chargers, EV2 and EV3 are admitted; EV1 remains waiting. With equal weights the scheduler treats urgency, degradation, grid stress and price equally. As a result, EV3 (which has moderate energy demand but lower degradation than EV1) is admitted instead of EV1 despite EV1's large energy requirement. EV2 remains top priority due to its short available time. This example highlights how weight selection affects admission hence equal weights reduces biased toward one parameter.

### *B. Stage-II: GA-based Power Scheduling*

GA is a population based metaheuristic inspired by the principles of natural evolution. It is widely adopted for complex optimization problems where the search space is nonlinear and nonconvex, as in EV charging scheduling with multiple objectives and constraints. In this work, GA is employed after the priority based charger assignment to optimize the charging/discharging power levels of the admitted EVs over the scheduling horizon. This two-stage design reduces computational complexity by limiting the GA search space to only those EVs granted access in Stage-I. The optimization problem expressed as minimizing a ojective function defined in equation 21 can be expanded as:

$$J = w_1F_1 + w_2F_2 + w_3F_3 - w_4F_4 \tag{27}$$

where $F_1$ represents the total charging cost under time of use prices, $F_2$ denotes the degradation cost associated with the assigned charging/discharging powers, $F_3$ measures the variance of the aggregate load profile, and $F_4$ quantifies user satisfaction. The following section discusses GA's next steps including initialization, crossover and mutation.

*1) Encoding and Initialization:* In the proposed framework, the charging and discharging schedules of all admitted EVs are encoded as real-valued chromosomes. Each chromosome is a vector of length $M \times T$, where $M$ is the number of EVs and $T$ is the number of discrete time slots in the planning horizon. The $j$-th gene of the chromosome corresponds to one decision variable $x_{i,t} = p_{i,t}$ (in kW) defined as

$$x_{i,t} = p_{i,t}, \quad \forall i \in \{1, \ldots, M\}, \ t \in \{0, \ldots, T-1\} \tag{28}$$

where $p_{i,t}$ denotes the charging or discharging power of EV $i$ at time slot $t$ (in kW). A positive value ($p_{i,t} > 0$) indicates charging from the grid to vehicle (G2V), a negative value ($p_{i,t} < 0$) corresponds to discharging to the grid (V2G), and $p_{i,t} = 0$ represents idle status. For each EV, the per-slot decision is bounded as $-P_{ref} \le p_{i,t} \le P_{ref}$ where $p_{ref}$ denotes the rated maximum charging/discharging capacity of EV $i$. Furthermore, genes outside the EV's availability window, i.e., before arrival time $T_i^{\text{arr}}$ or after departure time $t_i^{\text{dep}}$, are always set to zero. This ensures that no energy transaction is assigned outside the physical presence of the EV.

*2) Fitness Evaluation:* The quality of each chromosome is assessed using the fitness function that combines the four objectives considered here, (i) minimization of net energy cost (G2V purchase and V2G revenue), (ii) minimization of battery degradation cost, (iii) minimization of grid load variance, and (iv) maximization of user satisfaction. The corresponding objectives $F_1(X)$, $F_2(X)$, $F_3(X)$, and $F_4(X)$ are defined in Section IV.

*a) Constraint Handling:* To handle infeasible solutions arising from random initialization or genetic operators, penalty terms are imposed for:

- SoC violation: when $\text{SoC}_i(t)$ lies outside $[0, 1]$,

- Charger occupancy violation: when more than $M$ EVs are simultaneously active,
- Grid capacity violation: when aggregate load exceeds $P_{\max}$.

The total violation penalty is expressed as

$$\Omega(X) = \alpha_1 \sum_{i,t} V_{i,t}^{\mathrm{SoC}} + \alpha_2 \sum_t V_t^{\mathrm{occ}} + \alpha_3 \sum_t V_t^{\mathrm{grid}} \quad (29)$$

with $\alpha_1, \alpha_2, \alpha_3$ as penalty coefficients, which are tuned during experimentation while violation terms are the amount by which it exceeds the respective ranges. The overall fitness is then obtained as a weighted sum of the objective terms and penalties:

$$J = w_1 F_1(X) + w_2 F_2(X) + w_3 F_3(X) - w_4 F_4(X) + \Omega(X) \quad (30)$$

Once the fitness of each chromosome is evaluated, the GA employs evolutionary operators to guide the population toward improved schedules across generations.

*3) Selection:* A tournament selection mechanism is used to favor fitter chromosomes while retaining diversity in the population. In each tournament, a subset of chromosomes is randomly chosen and the one with the lowest fitness score $J$ is selected as a parent. This balances exploration and exploitation by allowing less fit solutions rarely during tournament.

*4) Crossover:* To generate new candidate schedules, pairs of parent chromosomes undergo simulated binary crossover (SBX). For each gene $x_{i,t}$, offspring inherit values that are intermediate to those of their parents with a distribution controlled by the crossover index $\eta_c$. This operator preserves continuity of the real-valued search space while enabling meaningful mixing of charging and discharging schedules. Crossover probability $p_c$ determines the likelihood that offspring are produced from a parent pair.

*5) Mutation:* To introduce additional diversity, polynomial mutation is applied to individual genes with probability $p_m$. For a selected gene $x_{i,t}$, the mutation operator perturbs its value by a small amount proportional to the distance from its lower and upper bounds $[-P_i^{\text{dis,max}}, P_i^{\text{ch,max}}]$. This controlled perturbation helps escape local optima while maintaining feasibility with respect to EV charging and discharging limits.

Together, these operators ensure a balance between exploitation of high-quality solutions (via selection and crossover) and exploration of new feasible regions in the search space (via mutation).

## References